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Labour mobility and plant performance in Denmark: the significance of related inflows

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Abstract

This paper investigates the impact of different types of labour mobility on plant performance, making use of the IDA-database that provides detailed information on all individuals and plants for the whole of Denmark. Our study shows that the effect of labour mobility can only be assessed when one accounts for the type of skills that flow into the plant, and the degree to which these match the existing set of skills at the plant level. We found that the inflow of related skills has a positive impact on plant performance, while inflows of similar and unrelated skills have a negative effect on plant performance. Moreover, intra-regional skilled labour mobility had a negative effect on plant performance in general, while the effect of inter-regional labour mobility depends on the type of skills that flow into the plant. We used a sophisticated indicator of revealed relatedness that measures the degree of skill relatedness between each pair of sectors on the basis of the intensity of labour flows between sectors. We made the same estimations using the more common NACE-based skill relatedness indicator. Although our main findings remained the same, we found that our revealed relatedness indicator generated stronger levels of significance.

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1 Introduction

Increasing attention is devoted to the meaning and significance of technological relatedness for innovation and economic growth. With technological relatedness, we mean that economic entities like firms or industries have a higher scope for interactive learning when there is some degree but not too much cognitive proximity between firms and industries (Nooteboom, 2000). This simple idea has been used as an input to explain a range of phenomena, like the emergence of new technology systems (Carlsson and Stankiewicz, 1991), the economic success of mergers and acquisitions (Ahuja and Katila, 2001), the performance of research collaboration networks (Gilsing et al., 2008; Leten et al., 2007), spatial clustering of industries (Boschma and Wenting, 2007), regional economic growth (Frenken et al., 2007), and the process of branching at the national (Hidalgo et al., 2007) and the regional level (Neffke et al., 2009).

Only very recently, this idea of relatedness has been incorporated into labour market studies. Labour mobility is often regarded as a key mechanism through which knowledge diffuses. Boschma et al. (2009) claim that the effect of labour mobility on plant performance can only be assessed when one accounts for the type of skills that flow into the plant, and the degree to which these match the existing set of skills at the plant level. Among other things, they showed in a study on Sweden that the inflow of new skills should be related (but not similar) to the skill portfolio of the plant to impact positively on plant performance.

Our paper has three objectives. The first objective is to test these ideas empirically in Denmark. We employ the so-called IDA-database that provides detailed information on individuals and plants for the whole Danish economy, and we will analyse close to 66,000 high-skilled job moves into almost 23,000 Danish plants in the period 1999-2003. We hypothesize that new employees that bring in work experience from the same industry will not really contribute to plant performance, because these do not add something new to the existing set of skills. When the new skills are unrelated, the plant cannot easily absorb these, and we expect the plant is unlikely to learn and benefit from it. By contrast, we expect the inflow of new skills that are related to the existing set of skills in the plant to have a positive effect on plant performance, because they offer real learning opportunities. In order to determine related inflows, we make use of a new and sophisticated measure of revealed relatedness between sectors that is based on the mobility of non-managerial skilled workers (Neffke and Henning, 2009). The second objective is to estimate the effects of geographical proximity on the relationship between labour mobility and plant performance. As expected, we find evidence that the effects of labour mobility on productivity growth of plants depend on whether new employees are recruited from within the same region or from other regions. The third objective is to compare these findings that are based on the more advanced revealed relatedness indicator with outcomes when the more common method of NACE relatedness is used. Among other things, our analysis shows that the results based on the revealed relatedness indicator reveal stronger levels of significance on the different variety measures.

The paper consists of four sections. First, we discuss the main literature on the relationship between labour mobility, relatedness and plant performance. Based on that discussion, we present our main hypotheses. Afterwards, we present the data, and explain which variables we have constructed, and which methodology has been used. Then, we present the main empirical findings. We conclude by drawing some conclusions and providing some suggestions for future research.

2 Labour mobility, relatedness and plant performance

To an increasing extent, labour mobility is regarded as a mechanism that enhances the competitiveness of firms and regions (e.g. Lawson (1999); Hudson (2005); Rodriguez-Pose and Vilalta-Bufi (2005); Dahl and Sorenson (2008)). Because individuals embody tacit knowledge they have acquired at work, job mobility is regarded to facilitate the dissemination of this type of knowledge (e.g. Almeida and Kogut (1999); Pinch and Henry (1999); Cooper (2001); Power and Lundmark (2004)). In this literature, the benefits of labour mobility are often assumed to exceed the downsides, known as labour poaching (Kim and Marschke, 2005; Combes and Duranton, 2006).

However, recent studies have observed empirically that a high rate of labour mobility may have negative effects on firms performance (e.g. Faggian and McCann (2006); Boschma et al. (2009)). Moreover, what is implicit in this literature is that the effect of labour mobility is almost taken for granted, as if the new employees are integrated in the organization of the firm without any major frictions, and as if the new employees will contribute to internal learning processes and the well-being of the firm (Wenting, 2008; Boschma et al., 2009). Little attention has been drawn to the types of knowledge and skills that are transferred between firms through job-hopping. In innovation studies, it is a well-known fact that firms require absorptive capacity to understand external knowledge and transform it into growth (Cohen and Levinthal, 1990). More recently, however, there is increasing awareness that absorptive capacity may not be sufficient for learning to take place. What might be more important is whether external knowledge is close, but not quite similar to the knowledge base of the firm. In this context, Nooteboom (2000) made the claim that inter-firm learning requires some degree of cognitive proximity between firms, to enable effective communication, but not too much cognitive proximity, in order to avoid cognitive lock-in.

This idea has recently been applied to labour mobility studies. In a study on the effects of labour mobility on plant performance in Sweden, Boschma et al. (2009) concluded that the effect of labour mobility of plant performance can only be assessed when one accounts for the type of skills that flow into the plant, and the degree to which these match the existing set of skills at the plant level. Based on the analysis of 101,093 job moves, they found strong empirical evidence that inflows of skills that were related to the existing knowledge base of the plant had a positive effect on plant performance, while the inflow of new employees with skills that were already present in the plant had a negative impact. More precisely, new employees with work experience in industries related to the sector of the plant, contributed to plant productivity growth, in contrast to new employees from the same sector and from unrelated sectors. Apparently, some degree of cognitive proximity between the new employee and the firm, but not too much of that, is required to ensure that labour flows will materialize in and contribute to the performance of firms.

The economic effect of labour mobility has also drawn attention from economic geographers. One reason is that the overwhelming majority of job moves occurs within a region (Power and Lundmark, 2004), implying that knowledge transfer via job mobility predominantly is a local process. Economic geographers have emphasized that labour mobility contributes significantly to new knowledge formation at the regional level. Since tacit knowledge follows people and their mobility patterns, this type of knowledge is considered to be spatially sticky and locally embedded (Gertler, 2003; Iammarino and McCann, 2006). Almeida and Kogut (1999) argue that inter-firm mobility of labour may be held responsible for knowledge spillovers in regions like Silicon Valley. In addition, labour mobility creates linkages between firms through social ties between former colleagues. These social relationships in turn facilitate knowledge flows between firms (Breschi and Lissoni, 2003). Since most of the job moves are intra-regional, these social networks are formed locally, and will enhance further knowledge accumulation at the regional level (Dahl and Pedersen, 2003). From this line of thought, it can be concluded that mobility of skilled labour plays an important role in understanding the economic benefits of agglomerations (Malmberg and Power, 2005).

Having said that, it remains uncertain whether new employees should come from the same region or from elsewhere to have the largest impact on firm performance. As noted above, economic geographers often claim that geographical proximity may be beneficial because it facilitates the understanding and implementation of new knowledge. In the literature, increasing attention is paid to the crucial role of extra-local linkages, since too much reliance on merely local knowledge may result in lock-in that may be harmful to the performance of firms and regions (e.g. Bresnahan et al. (2001); Asheim and Isaksen (2002). To our knowledge, this idea has not yet been applied to labour mobility. Following Boschma et al. (2009), we argue once again that the effects of labour mobility on firm performance can only be accounted for after differentiating between types of labour inflows, in this case depending on whether new employees are recruited from the same region or from other regions.

Boschma et al. (2009) found evidence that intra-regional labour mobility is not per se a good thing, as often assumed by the economic geography literature. Labour mobility crossing regional boundaries is not necessarily good or bad for firm performance either. Once again, that depends on the types of skills that flow into the firms, and to what extent these match the existing skill portfolio of firms. Their study on Sweden clearly showed that inflows of unrelated skills only contributed to plant performance when these are recruited from the same region. This was explained by the fact that the problem of communication inherent to hiring new employees with skills that are totally new to the plant is even more pronounced when these are recruited from other regions. Moreover, Boschma et al. (2009) found that labour mobility across regions only had a positive effect on productivity growth of plants when this concerned new employees with related skills.

3 Method

3.1 Data and Sampling

We apply these ideas when accounting for the effects of labour mobility on the performance of firms. The basic idea is that inflows of new skills are required to avoid lock-in at the firm level, because too much reliance on internal skills may be harmful. Doing so, we need to specify which types of skills are brought into the plant by new employees, and to what extent these newly acquired skills add to the existing knowledge base of plants. Following this line of thought, we expect that no real learning will take place when the newly acquired skills are the same or when they are unrelated. Therefore, we claim that the inflow of new skills should be related, but not similar to the existing knowledge base of the plant to have economic impact, because in those circumstances, real learning opportunities are present.

For the empirical analysis, we rely on the Danish Integrated Database for Labour Market Research (IDA). IDA is a longitudinal and universal linked employer-employee dataset constructed from government registers and maintained by Statistics Denmark (DST). The database contains detailed information on *all* individuals and *all* plants in Denmark from 1980 and onwards. The longitudinal character enables us to identify labour mobility flows by comparing employer-employee relationship in consecutive Novembers.[1] A change in this relationship would indicate a move.[2] As a result, short-term employment relationships within a year, e.g. from December until August, cannot be identified. From this database we selected a total of 22,788 plants active in manufacturing and services that over a five-year period, i.e., 1999-2003, experienced an inflow of highly skilled employees.

Earlier studies have shown that Denmark, together with the Anglo Saxon countries, has one of the most flexible labour markets; i.e., job durations are shorter and the job-to-job changes are higher compared to European average (Schettkat, 1997; Albæk and Sørensen, 108; Bingley et al., 1999; Madsen, 2002; EUROFOUND, 2006). Other Nordic countries, e.g. Finland and Sweden, show a slightly different pattern since workers have longer tenure compared to Denmark (Madsen, 2002). Roughly 30 percent of employees are hires, which means that they work in a different plant compared to the previous year, and the percentage of separations between two consecutive years is approximately the same (Albæk and Sørensen, 108; Bingley et al., 1999). Even in times of recession the share of hires is considerable, i.e. around 25 percent (Albæk and Sørensen, 108; Bingley et al., 1999). It has been said that the Danish institutional setting of high social security in combination with low employee protection, called flexicurity, is an important factor in explaining these high mobility rates (Schettkat, 1997; Bingley et al., 1999;

[1] Statistics Denmark provides only yearly observations. The employer-employee relationships are identified in November; therefore, we can only identify the employer-employee relationships that exist in November.

[2] Job changes are only calculated based on the primary occupation of the individual, which is predominantly the occupation that generates their highest income. Other employment relationships will be ignored.

Madsen, 2002). However, the short job duration might also be explained by the Danish industry structure that is characterized by relatively small firms and a low retirement age (Andersen and Svarer, 2007).

The identification of unique plants becomes an important issue whenever one wants to identify job movers. A plant is an abstract and complex entity that is subject to different type of changes, i.e. change in employee composition, mergers and acquisitions, separation, etc. In many of these cases, IDA maintains the same plant identity number. For those cases in which the plant identification number changes we need to identify which individuals follow this identity change and therefore cannot be regarded as job-movers.

Since we are interested in the effect of high-skilled labour mobility we included only those plants that experienced an inflow of high skilled workers that have an established position on the labour market. For this reason, the workers need to fulfil the following criteria: (i) earn a taxable income of 150,000 DKK[3], (ii) are at least 25 years of age, (iii) have a position of at least 20 hours a week, and (iv) are registered to have changed plant. This last requirement implies that individuals without any registered work experience, or that experienced a long spell of unemployment, will not be included. To identify highly skilled job-movers, additional requirements are added; these individuals have to (v) hold a university degree or belong to the top 20 percent income earners. The income requirement is added because key individuals do not necessarily have an academic training.

In addition to the criteria on highly skilled job-movers, we also included plant criteria. First, we focus on plants in manufacturing and services, i.e. two-digit NACE codes 15-37 and 60-74. In addition, the four-digit NACE industry codes of the plants are crucial for creating the different variety measures. Consequently, information on industry affiliation should be available for all the plants in the sample. Second, we want to identify the effect of mobility on the productivity growth of plants; therefore, financial data needs to be available in two points in time, i.e. in the year in which a highly skilled inflow is observed and two years after. Because this data is only available on the firm level we remove all the plants that changed firm identity during these two time periods. We also remove new founded plants in already existing firms because these plants are experiencing only an inflow of workers. Finally, the performance of start-ups and young firms are heavily

[3]This is the value for 1999; for the following years this income is inflated with the Consumer Price Index with 1999 as the base year.

influenced by their liabilities of newness (Stinchcombe 1965); for this reason, we omit all firms younger than five years.

In Table 1, an overview is presented on the number of plants that fulfil the above-mentioned criteria during the period 1999-2003. The number of plants that experience an inflow of at least one high skilled worker varies between 4,100 and 4,800 per year, leading to a total of 22,788 observations over the five-year period. This is around 2.5 percent of all the plants that can be identified in IDA for the entire period. It should be noted that many plants are excluded from the sample despite of experiencing an inflow of skilled workers, e.g. due to lack of accounting data. The yearly number of highly skilled job-movers in the sample varies between 11,500 and 14,000, which is just below five percent of the entire workforce that is present in these plants. Each plant welcomes close to three high skilled workers on average; although the inflow decreases over the five-year period. Both the number of plants and highly skilled job movers are based on yearly observations. As a result, some plants will appear more than once in the sample. In total there are 11,955 unique plants, i.e. the number of unique plant identification numbers in the five-year period, 5,733 plants (47.95 percent) experience a high-skilled inflow in more than one year; 519 plants (4,34 percent) experience an inflow in all years.

Table 1 around here

3.2 Dependent Variable: Labour Productivity Growth

In a similar fashion as Boschma et al. (2009), the performance measure that serves as the dependent variable in the regression analyses is labour productivity growth. To measure labour productivity growth we calculated the growth of value added per worker. The Danish accounting database reports this value added only on the firm level. However, 7,367 plants (32.34 percent) in the sample are part of a firm that consists out of multiple plants. The value added of these plants was determined by distributing the firms value added among the plants according to the distribution of wages. Afterwards, the value added was divided by the full time equivalent of the employees in these plants. As a last step, the productivity per person in a specific plant was subtracted from the productivity per person in the same plant two years ahead in time to identify the growth of labour productivity. Similar to Boschma et al. (2009) we use a two-year lag because we expect that the impact of labour mobility will materialize after a few years.[4] Log values of this

[4]On top of that, incorporating a one-year lag did not present strong level of significance while a three-year lag showed similar results

measure are used to reduce the impact of skewed distributions.

3.3 Independent Variables

The independent variables constructed for the analysis are all measured at the beginning of each two-year period. To estimate the values for the inhouse competence portfolio we relied on the four-digit NACE industry classification associated with the plant and the work experience of those employees that were employed for at least 20 hours a week in that given year. We decided to include a larger set of employees than just skilled workers for two reasons. First, the number of skilled workers that are already present is relatively low; consequently the inhouse skilled worker variety measure is heavily correlated with the inflow skilled worker measure. Second, it gives insights in the impact of the entire plant portfolio. For the skilled inflow we only measured the variety measures for those employees that are identified as highly skilled and did not work in the plant in the previous year. During the period 1999-2003 we identified 468 different four-digit NACE industry codes in the entire Danish economy out of which we identify 205 categories in manufacturing and 53 categories in services.

Before assessing the relative importance of these different types of external knowledge though, we need to assess the impact of intra-firm learning on firm performance (Maskell, 2001; Sternberg and Arndt, 2001). While it is common knowledge that human capital at the firm level (as proxied by the level of research or the educational level of the personnel) positively impacts on firm performance, there is still little understanding of whether particular types of competence portfolios at the plant level enhance the performance of plants (Lacetera et al., 2004). While absorptive capacity is certainly needed to understand and implement the new skills at the plant level, we expect plants with employees with related or complementary competences to perform better, because this type of portfolio will particularly enhance interactive learning between employees within a plant, in contrast to plant portfolios that consist of employees with either similar or unrelated competences.

To create the measure for the degree of similar, related, or unrelated industry experience, we identified the employment relationships of the employees in the last five years. This experience can vary from employees that have no previous work experience, e.g. a new entry into the labour market, to employees that are highly mobile and have experience in a range of different industries. Whenever an employee, during the last five years, gained experience in multiple industries, which is the case for 28,50 percent of all highly skilled job-movers, the relatedness is determined by the most related industry experience. Thus, if a person has worked for two plants, one being related and the other unrelated, the experience of this individual is regarded as related. Whenever an employee worked in two plants out of which one can be affiliated with the same four-digit NACE industry code, the skills of this person will be treated as similar.

Having said this, we now explain how the competence portfolio and skilled inflow measures are calculated. In total we created 19 different measures: one measuring the share of sameness, six measuring the overall level of similarity, relatedness, and unrelatedness of the competence portfolio and skilled inflow, and twelve measures where the six overall measures are separated in intra- and inter-regional movement.

To determine whether this experience is intra- or inter-regional, thereby testing the impact of geographic proximity, we identified local labour market regions within Denmark. Whenever an employee acquired this experience within the same local labour market the experience is intra-regional, otherwise the experience is inter-regional. To identify these local labour markets we followed the approach set out by (Andersen, 2002). She defined a local labour market as an area that is relatively closed based on the commuting patters of workers. Based on the commuting patterns of these workers in all industries in 1995, she identified 35 different labour market regions. However, labour market regions are not fixed regional units because commuting patterns vary between industries and over time. Since we are interested in manufacturing and services, and look at a different period in time, the 276 municipalities[5] are assigned to a total of 22 different local labour market regions. A list with the municipalities that belong to each labour market region is presented in Appendix I. In the previous paragraph we mentioned that there is a ranking based on the level of relatedness, i.e. whenever a person has experience in a similar and in a related industry the set of skills will be regarded as similar. When including the geographical dimension the level of relatedness outweighs the geographical dimension, i.e. if a person has experience in a related industry in the same region and similar industry experience in another region the set of skills will be regarded as similar and inter-regional. The ranking will thus be as follows: intra-regional similarity, inter-regional similarity, intra-regional related variety, inter-regional related variety, intra-regional unrelated variety, and inter-regional unrelated variety. Before we calculate the different variety measures we constructed three measures that indicate the

[5]This is the number of municipalities from before the Danish municipality and regional reforms of 2007 where the number was reduced to 98 municipalities.

size of the skilled inflow. The first measure is a total skilled inflow by taking the log on the number of skilled inflows. Making a distinction on whether this flow is intra- or inter-regional creates the two remaining variables. However, if the inflow is intra- or inter-regional will dependent on the flow of the most related industry. So, if a person has similar skills from another region and unrelated from the same region the skill flow is identified as inter-regional.

Despite the fact that labour mobility is high within Denmark, a large majority of the employees that worked in the plant in period t also worked in this plant in the previous year, t_{-1}. All these non-movers would, when applying the most related industry principle, be regarded as employees with similar industry experience. The problem that arises is the high value of similar skills in the competence portfolio. For this reason, we only include the industry experience in those plants that are not equal to the plant in which they are currently active. Nevertheless, we included a measure to indicate the share of employees in period t that also worked for this plant in t_{-1}, i.e. the share of sameness (Inhouse Same).

$$InhouseSame = \frac{n_{same}}{N} \tag{1}$$

n_{same}= Number of employees that worked for the plant in t_{-1}.
N= total number of employees that works at least 20 hours a week

The remaining 18 variety measures are created for both the competence portfolio and the skilled inflow. These variables will be calculated by linking the employees most related industry experience to the industry in which the plant is active; however, as indicated earlier, we do not include the experience acquired in the plant for which the person is currently active. The degree of portfolio similarity (Inhouse Sim) is measured by taking the share of workers that during the last five years worked in another plant that was active in the same four-digit NACE industry class as the current plant.

$$InhouseSim = \frac{n_{sim}}{N} \quad (2)$$

n_{sim}= Number of employees with the most related experience in the same four-digit NACE industry.
N= total number of employees that works at least 20 hours a week

In addition, we identify whether this similarity is intra-regional (Intra Inhouse Sim) or inter-regional (Inter Inhouse Sim). IDA only provides information on the main output for each plant; consequently, each plant has only one industry code. For this reason, we cannot use an entropy measure to calculate the different variety measures as the experience of the workers can only be compared to this single industry code. Instead, we sum the number of workers that are similar, related, or unrelated compared to the industry in which the plant is active. Entropy is more suitable to calculate the degree of variety among the different members in the organization; however, with this measure the composition can be similar in terms of their experiences but their experiences could still be unrelated compared to the industry in which they are currently active. For measuring the inflow of similar skills (Inflow Sim) we count the number of highly skilled workers that entered the plant and, during the last five year, had experience in a plant that was active in a similar industry. Also here we make a distinction between intra-regional (Intra Inflow Sim) and inter-regional similarity (Inter Inflow Sim). Log values of this measure will be used to control for high degrees of inflow similarity.

The degree of related variety (Inhouse Relvar) is measured by taking the share of employees that worked for a plant that was active in a related industry.

$$InhouseRelvar = \frac{n_{rel}}{N} \quad (3)$$

n_{rel}= Number of employees with the most related experience in a related four-digit NACE industry.
N= total number of employees that works at least 20 hours a week

This related variety is not, as earlier studies have done, measured on the extent industry classes can be considered related based on the standard industry classification. This approach will grasp much but not all the industry relatedness within an economy because the degree of relatedness can move beyond the two-digit NACE industry class. Instead, we used a measure of revealed relatedness of industry codes based on the mobility of skilled non-managerial labour (Neffke and Henning, 2009). This approach takes the point of departure in the skills of the workers and in the degree these skills are transferable between different industries. Neffke and Henning (2009) argues that skilled non-managerial workers will, when they search for a new job, move to industries in which their skills are valued; not doing so might lead to the destruction of their human capital. A high rate of mobility of highly skilled non-managerial workers to a specific industry would indicate a high valuation of skills, less human capital destruction, and thus a high degree of relatedness.

To identify which industry pairs are related they constructed a matrix based on the 435 different four-digit NACE industries in the Swedish economy, creating a total of 188,790 unique industry pairs. For each industry pair they identified the total number of highly skilled non-managerial job movers during the period 2004-2007. Neffke and Henning (2009) argues that revealed relatedness cannot be measured only based on these raw labour flows because other industry characteristics determine these labour flows and they need to correct for these effects. In doing so, they construct a revealed relatedness measure based on the degree by which observed labour flows are in excess of predicted labour flows. The revealed relatedness index is thus formulated as:

$$RSR_{ij} = \frac{F_{ij}^{obs}}{\hat{F}_{ij}} \tag{4}$$

where F_{ij}^{obs} is the observed labour flow and $\hat{F}_{ij}$ the predicted labour flow. The predicted labour flows are calculated by using a zero inflated negative binominal regression analyses. There are three motivations for using this approach: (i) labour flows can never be negative, (ii) they are always integer, and (iii) the majority of industry pairs do not experience any flow of labour. The industry effects for which they control are size, because the size of the labour flow is positively correlated with the size of the industry, and wage, because higher wages are an important incentive for changing jobs.

A problem is that the information on some industry combination is too limited to claim revealed relatedness. For this reason, they quantified a level of confidence that can be linked to the revealed relatedness estimates. To do so they treated the mobility flow as a choice of each moving highly skilled individual to either stay in the same industry or to move to any of the other 434 industries. The alternative expression they constructed is:

$$RSR_{ij} = \frac{P_{ij}^{obs}}{\hat{P}_{ij}} \tag{5}$$

where the denominator and numerator of Equation 4 are divided by $emph_i$, i.e. the number of employees in the industry of origin. Afterwards, they calculate if the observed relative frequency, P_{ij}^{obs} , is significantly higher than the expected probability, $\hat{P}_{ij}$.

With a revealed relatedness index of more than one and a significance level of 10 percent, they identified 9,919 related industry pairs; many of these industry pairs are both intuitively and according to the industrial classification system related. The analyses conducted in this article will rely on the same industry pairs but making a few alterations.[6] First, even though the Swedish and the Danish four-digit NACE codes are similar, a small recoding is necessary because some industry codes do not match. Second, two type of industries, i.e. public sector and hotel and restaurants, are removed from being related to other two-digit NACE industry. These two industries employ a wide range of people, which links these industries to many other industries. Due to the more general nature of these skills we decided to recode these industries as not being related to manufacturing and services.[7] As a result of this transformation process we identify a total of 7,750 directed and related industry pairs.

[6]There are two reasons for using the Swedish industry pair matrix as an instrument for the revealed relatedness of Danish industries. First, if we would have used the revealed relatedness measure based on the high skilled job mobility in Denmark we would have run the risk of endogeneity as the method for determining the revealed relatedness is similar to the method of establishing the degree of related and unrelated skills that are present in a plant. In addition, the mobility patterns of skilled workers in Sweden will have no immediate impact on the performance of the Danish plants in our sample. Second, there would be no reason to assume that industry specific skills would vary between Sweden en Denmark with the only exceptions that some industries are not present in the Danish or Swedish economy..

[7]The analyses will show that the level of significance improves when the recoded related industry pairs are used.

To measure the inflow of related skills (Inflow Relvar), we count the number of high-skilled job movers that moved into the new plant, and can at best be associated to have worked for one of the related industries. For both the inhouse and inflow related variety we make a distinction whether this experience is intra- or inter-regional. The variety measures that remain are those that are regarded unrelated. The degree of unrelated industry experience (Inhouse Unrelvar) is calculated by taking the share of employees that, in the last five years, have work experience in plants that were not active in a similar or related industry compared to the industry in which they currently are employed.

$$InhouseUnrelvar = \frac{n_{unrelvar}}{N} \tag{6}$$

$n_{unrelvar}$= Number of employees with experience in an unrelated four-digit NACE industry.
N= total number of employees that works at least 20 hours a week

The inflow of unrelated skills (Inflow Unrelvar) is the count of highly skilled job movers into the plant that did not work in a similar or related industry in the last five years. Also here a distinction is made whether this unrelated experience is intra- or inter-regional.

3.4 Control Variables

In addition to the above-mentioned explanatory variables, we need to control for other factors that explain labour productivity growth. Productivity numbers vary significantly across different industries. To control for any industry effects, we use industry fixed effects based on the two-digit NACE industry classification, creating a dummy variable with the value one whenever the plant is active in this specific industry. In total we identify 34 different two-digit NACE industries. The most represented industry is Other Business Services including just over 23 percent of the entire sample. This large industry will serve as the benchmark to which the other dummies will be compared.

Similar differences in productivity can be observed for the geographic location of a plant; for this reason, location fixed effects variables are added to the model. This is done by creating dummy variables for each of the 22 different local labour markets that we identified earlier in this paper. As expected, the labour market region that includes

Copenhagen is by far the most represented in the sample. In total 45 percent of all plants are located in this area, which covers the entire island of Zealand. In addition, 55 percent of all the highly skilled job-movers are active in this local labour market. This local labour market region will serve as the benchmark category.

This leaves us with one remaining fixed effects variable, i.e. the year in which the high-skilled inflow is observed. For this year fixed effects a dummy variable is created that gives the value one for the year in which the move is observed. The year 1999 will serve as the benchmark category.

Productivity is also influenced by the size of the plant and the overall age of the firm. To control for these two effects we included a measure indicating the number of employees in the firm and a variable for the age of the firm. Because the growth in productivity can also be explained by a change in labour force and an increase in capital, we included two measures to control for this change, i.e. a growth in the number of employee and fixed assets between t and t_{+2}. These fixed assets are calculated in a similar fashion as the labour productivity growth. Finally, to better asses the competence portfolio we also include a measure that indicates the share of employees with a bachelor degree or higher. Table 2 presents the descriptive statistics for these variables. The method by which we created the different dependent variables we run the risk of multicollinearity; however, multicollinearity tests have indicated that this is not the problem since the variance inflation factor stays below the critical boundary of five.

Table 2 around here

3.5 The Model

For the analyses we use an ordinary least square regression model with fixed effects estimates. The fixed effects estimators in the model are: year fixed effects, two-digit NACE fixed industry effects, and year fixed effects. These fixed effects estimators are introduced to capture parts of the unobserved heterogeneity associated with studies on labour productivity. The main interest of this paper is to test if the results on the impact of a diverse set of skills inflow, as found in Boschma et al. (2009), also hold for the Danish case, but slightly altering the analysis by using revealed relatedness measures and taking into account multiple years of work experience. For this reason, the model only includes those plants that experience an inflow of highly educated or high-income earners; because it is most likely that knowledge transfers between plants occurs through the mobility of this type of employee.

All the models in the analyses will be weighted by employment size. The motivation for doing so is the large share of small plants in the sample (50 percent of the firms in the sample has less than 25 employees); however, as the top 10 percent largest companies employ just over 50 percent of all employees in the sample, they only account for a small part of all the employees. By including weights the larger plants will receive a larger proportional share of the total explained variance.

4 Empirical Results

The effects of the plant characteristics and the diversity in the competence portfolio on labour productivity growth are presented in Table 3. Model A only includes the control variables for the analysis and shows the expected effects for most of the variables. The age of the firm appears to have the strongest impact on labour productivity growth, followed by the size of the plant. Two other variables, i.e. growth of labour and growth in fixed assets, also contribute significantly to the growth of productivity. The consequence of using large sets of micro data is the large degree of unobserved heterogeneity, even when including multiple fixed effects variables. Adding multiple years into the model increases the noise even further, which explains the low values for R-Squared; nevertheless, the significance level of the variables remains the same when including the competence portfolio and skilled inflow variables.

Surprisingly, the share of academic trained employees has no significant effect on labour productivity growth. The study on the impact of labour mobility in Sweden showed a positive effect of education on labour productivity growth (Boschma et al., 2009). This can, however, be explained by the negative impact of skilled mobility inflow. This variable includes a fair share of highly educated individuals. Whenever the inflow variable is included the share of highly educated turns positive, although only on the ten percent significance level. Additionally, the local labour market that includes Copenhagen outperforms most of the other labour market region when it comes to labour productivity growth. In addition, the service industry seems to experience higher levels of productivity growth than manufacturing. These last two variables are, however, not reported in Table 3.

In Model B1 and B2 we include the overall competence portfolio based on the industry experience of the employees in the plants, where Model B2 makes a distinction whether the experience is from within or outside the same local labour market. To calculate the portfolio we included all the employees that worked at least 20 hours a week. The only variable that appears to have a positive and significant effect on labour productivity growth is Inhouse Same. The other competence portfolio measures, i.e. similarity, related variety, and unrelated variety are not significant. Apparently, the presence of variety in industry experiences does not contribute significantly, neither positive nor negative, to the performance of the plant. A high share of employees worked in this plant in the previous year. A possible explanation is that the impact on a diverse skill set of these employees already materialized. In addition, it might be necessary for a firm to have all skills present in the plant; especially experience within the same industry.

Table 3 around here

We are, however, predominantly interested in the impact of skilled labour mobility, as it is argued that this contributes to the knowledge exchange and learning between firms. To test the impact of this skilled labour mobility we created four models, which are presented in Table 4. In Model C1 we estimated the effect of the total skilled labour inflow while in Model C2 we differentiate between the specific skills that follow with the labour mobility. Model C1 shows a negative impact on the inflow of highly skilled workers. This effect is in line with the findings of (Boschma et al., 2009); however, it stands in contrast with the literature that argues in favour of high skilled labour mobility. (Boschma et al., 2009) argues that it is not labour mobility per se that has a positive impact but rather the collection of skills that are associated with the inflow. When taking into account the type of skills, as presented in Model C2, we see that this indeed is the case. In general,[8] negative effects of labour mobility can be attributed to the recruitment of highly skilled labour that has experience in similar and unrelated industries. Relatedness, on the other hand, appears to have a positive impact on labour productivity growth, although only on the ten percent significance level.

[8]The results show the overall impact of the variety in skill set over a five-year period. During this period Denmark suffered a period of high growth and a recession. The impact in individual years will, for this reason, differ. Because different industries and different size firms react differently to periods of growth and period of recessions the difference in impact will also be visible on these plant characteristics. Nevertheless, the overall picture shows a clear impact of similarity, related and unrelated variety on the performance of these plants.

In Model D1 and D2, we test the impact of geographical proximity. Here we take a point of departure in Model C1 and C2 but distinguish if the highly skilled job-movers come from the same or from another labour market region. In Model C1, we observed that the inflow of skilled workers had a negative impact on labour productivity growth. Model D1 shows that the negative effect can be attributed to the inflow of skilled workers from the same labour market region. The inflow of skilled workers from other labour market regions does not have a significant impact on labour productivity growth. This result stands in contrast with the findings of Boschma et al. (2009), where inter-regional inflow of labour appeared to be negative. Nevertheless, the effect is not surprising since the literature, next to regarding geographic proximity as beneficial, also hints upon the potential negative effect of intra-regional linkages due to spatial lock-in (Boschma, 2005). Our result is also supported empirically by a study on labour mobility in the Finnish high-tech industry, where local labour flows have a negative impact on the innovative performance of firms (McCann and Simonen, 2005).

The inflow of similar skills showed to have a negative effect on the performance of plants. This, however, does not hold when making a distinction between intra- and inter-regional inflows. Model D2 shows that the inflow of employees with similar skills from the same local labour market has a negative effect on labour productivity growth. This result is in line with Boschma et al. (2009). Interestingly, the inflow of similar skills from other labour market regions has a significant positive effect on labour productivity growth. The positive effect comes as a surprise. We would have expected that the recruitment of employees with similar skills would reduce the negative impact but not to turn it around as it does in the analysis.

The inflow of related skills proved to have a positive effect on labour productivity growth, even though this positive effect is only visible on the ten percent level of significance. By adding a geographical dimension to the inflow of these related skills, we observe a non-significant effect whenever the inflow is from the same labour market region; in addition, a strong positive effect appears whenever the highly skilled job-mover comes from a different labour market. We expected to find a positive effect in both situations comparable to the study of Boschma et al. (2009). Nevertheless, the recruitment of related skills scores best compared to the inflow of similar and unrelated skills in each geographical dimensions.

In Model C2, we observed that the inflow of unrelated skills harms the performance of plants. This negative effect remains present whenever a distinction is made between intra- and inter-regional inflows, as shown in Model D2. The negative impact of recruiting unrelated high skilled workers from other labour market is not surprising given the combination of two types of distance, i.e. cognitive and geographic distance, leading to problems in communication. This finding is also in line with the results presented in Boschma et al. (2009). Recruiting individuals from the same local labour market does not solve this problem; however, it appears that the geographic proximity mitigates this negative impact.

Table 4 around here

The third objective of this paper is to compare the findings of the more advanced revealed relatedness measure, which has been constructed by Neffke and Svensson-Henning (2009), with the commonly used method of NACE relatedness. Appendix II and Appendix III present the ordinary least squares regression analyses with fixed effect method using the variety measures that have been calculated based on this NACE relatedness. By comparing the different models, we observe that the coefficients and the level of significance of the control variables are very much the same. Whenever we relay our focus towards the variety measures we can see that overall both relatedness measures have the same impact on labour productivity growth. There are, however, some clear differences in the level of significance and the magnitude of the effect. First, we observe that the coefficients point stronger towards the expected effect of the various variety measures, i.e. related variety shows higher coefficient values and unrelated variety presents lower coefficient values. On top of that, the level of significance is higher when using the revealed relatedness measure.

Thus, both NACE relatedness and revealed relatedness are good indicators on how different set of skills impact on the performance of plants. It basically indicates the strong robustness of our findings concerning the effect of related variety. Revealed relatedness, however, appears to be a more accurate measure, because it generates stronger coefficients and levels of significance.

5 Conclusions

This paper has made an attempt to contribute to the growing literature that assesses the impact of labour mobility on plant performance. Making use of unique Danish data, our study provides strong evidence that the effect of labour mobility can only be assessed when one accounts for the type of skills that flow into a plant, and the degree to which these new skills match the existing set of skills in the plant. To assess the degree of relatedness between new and existing skills, we used a sophisticated indicator of revealed relatedness that determines the degree of skill relatedness between sectors on the basis of mobility of non-managerial skilled workers between sectors.

As expected, we found that the inflow of related skills impacts positively on plant performance, while inflows of skills that are similar or unrelated to the existing set of skills in the plant have a negative effect on plant performance. Moreover, we found evidence that the effect of labour mobility on plant productivity growth depends on whether new employees are recruited from the same region or from other regions. Intra-regional skilled labour mobility had a negative effect on plant performance more in general, which is a remarkable outcome that tends to contradict claims by the economic geography literature. However, the effect of inter-regional labour mobility depends on the type of skills that flow into the plant: the inflow of similar and related skills recruited in other regions impacted positively on plant performance, but negatively when it concerns workers with unrelated skills.

We also tested whether the use of the more sophisticated indicator of revealed relatedness generated better results, as compared to the more common NACE-based relatedness indicator in other studies. Although the main findings basically remained the same, we found that our revealed relatedness indicator generated stronger levels of significance.

These findings call for further research. First of all, it would be interesting to see whether these hypotheses are confirmed when one looks at particular sectors. Do these findings differ from one sector to another? And do these also differ from one stage of the industry life cycle to the next? One could hypothesize that in the early stages, new firms need labour from related industries, like new firms also tend to benefit from entrepreneurs that have acquired experience in related industries (Boschma and Wenting, 2007; Klepper, 2007). And secondly, this kind of labour mobility studies could also contribute to the spatial externalities literature. Do regions with a high degree of related labour mobility enhance regional growth? We believe that these and others questions would certainly increase our understanding of how labour mobility affects the economic performance of plants and regions, and to what extent relatedness is a crucial input to that.

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Table 1: High-Skilled Job Movers and Plants 1999-2003

YEAR	PLANTS	TOTAL EMPLOYEES	HIGH SKILLED INFLOW
1999	4,747	300,610	13,833
2000	4,744	295,376	14,048
2001	4,781	279,478	13,910
2002	4,409	263,151	12,350
2003	4,183	264,411	11,580
Total	22,788	1,403,026	65,721

Table 2: Variable Description (n=22,788)

VARIABLES	DESCRIPTION	MEAN	SD	MIN	MAX
Productivity Growth (log)	Change in labour productivity t and t+2 (log)	0.84	11.26	-21.36	18.54
Growth of Labour (log)	Change in employees between t and t+2 (log)	-0.23	2.01	-7.7	7.64
Growth of Assets (log)	Change in fixed assets between t and t+2 (log)	-0.31	11.31	-21.35	20.26
Plant Size (log)	Number of empl in the plant (log)	3.29	1.26	0	8.79
Firm Age (log)	The age of the firm in the number of years (log)	2.78	0.66	1.61	4.72
High Education Ratio	Share of empl with at least a bachelor degree	0.2	0.24	0	1
Total Skilled Inflow (log)*	Total number of highly skilled inflows (log)	1.07	0.58	0.69	5.55
Total Intra-regional Skilled Inflow (log)*	Total number of highly skilled inflows from within the same local labour market region (log)	0.86	0.63	0	5.53
Total Inter-regional Skilled Inflow (log)*	Total number of highly skilled inflows from a different local labour market region (log)	0.32	0.49	0	4.16
Inhouse Same	Share of empl that worked in the plant in the previous year.	0.71	0.25	0	1
Inhouse Sim	Share of empl with similar industry experience from at least one different plant.	0.26	0.24	0	1
Inhouse Relvar	Share of empl that do not have similar but at least related industry experience from different plants.	0.14	0.19	0	1
Inhouse Unrelvar	Share of empl with solely unrelated industry experience from different plants.	0.23	0.2	0	1
Intra Inhouse Sim	Share of empl with similar industry experience from at least one different plant in the same labour market region	0.22	0.22	0	1
Intra Inhouse Relvar	Share of empl that do not have similar but at least related industry experience from different plants in the same labour market region	0.12	0.18	0	1
Intra Inhouse Unrelvar	Share of empl with solely unrelated industry experience from different plants in the same labour market region	0.19	0.18	0	1
Inter Inhouse Sim	Share of empl with similar industry experience from at least one different plant in a different labour market region	0.03	0.09	0	1
Inter Inhouse Relvar	Share of empl that do not have similar but at least related industry experience from different plants in a different labour market region	0.02	0.06	0	1
Inter Inhouse Unrelvar	Share of empl with solely unrelated industry experience from different plants in a different labour market region	0.04	0.08	0	1
Inflow Sim (log)*	Number of highly skilled inflows with similar industry experience (log)	0.44	0.58	0	5.19
Inflow Relvar (log)*	Number of highly skilled inflows with no similar but at least related industry experience (log)	0.35	0.52	0	4.29
Inflow Unrelvar (log)*	Number of highly skilled inflows with solely unrelated industry experience (log)	0.51	0.59	0	4.72
Intra Inflow Sim (log)*	Number of intra-regional highly skilled inflows with similar industry experience (log)	0.34	0.54	0	5.19
Intra Inflow Relvar (log)*	Number of intra-regional highly skilled inflows with no similar but at least related industry experience (log)	0.27	0.48	0	4.29
Intra Inflow Unrelvar (log)*	Number of intra-regional highly skilled inflows with solely unrelated industry experience (log)	0.41	0.55	0	4.72
Inter Inflow Sim (log)*	Number of inter-regional highly skilled inflows with similar industry experience (log)	0.12	0.33	0	3.95
Inter Inflow Relvar (log)*	Number of inter-regional highly skilled inflows with no similar but at least related industry experience (log)	0.09	0.26	0	3.4
Inter Inflow Unrelvar (log)*	Number of inter-regional highly skilled inflows with solely unrelated industry experience (log)	0.14	0.34	0	3.83

*Due to the high frequency of zeros we used the following log transformation $log(x+1)$.

Table 3: Fixed effects regressions on the effect of competence portfolio based on industry experience on productivity growth for all plants with inflow of skilled workers (revealed relatedness)

PRODUCTIVITY GROWTH	MODEL A1			MODEL B1			MODEL B2		
	Estimate		S.E	Estimate		S.E	Estimate		S.E
Intercept	-1.978	***	0.505	-2.443	***	0.748	-2.600	***	0.758
Year 2003	-0.135		0.227	-0.112		0.227	-0.115		0.227
Year 2002	-0.009		0.227	-0.006		0.227	-0.008		0.227
Year 2001	-1.52 0	***	0.222	-1.505	***	0.223	-1.510	***	0.223
Year 2000	0.321		0.218	0.354		0.218	0.354		0.218
Year 1999	*Benchmark*			*Benchmark*			*Benchmark*		
Growth of Labour (log)	0.109	***	0.023	0.112	***	0.023	0.113	***	0.023
Growth of Assets (log)	0.155	***	0.006	0.156	***	0.006	0.156	***	0.006
Plant Size (log)	0.269	***	0.065	0.214	***	0.066	0.226	***	0.067
Firm Age (log)	0.871	***	0.109	0.847	***	0.111	0.840	***	0.111
High Education Ratio	0.264		0.627	0.338		0.632	0.317		0.634
Inhouse Same				1.175	***	0.447	1.286	***	0.455
Inhouse Sim				-0.383		0.455			
Inhouse Relvar				-0.455		0.643			
Inhouse Unrelvar				-0.061		0.640			
Intra Inhouse Sim							-0.588		0.471
Intra Inhouse Relvar							-0.379		0.676
Intra Inhouse Unrelvar							0.201		0.714
Inter Inhouse Sim							2.314		1.473
Inter Inhouse Relvar							-0.025		2.284
Inter Inhouse Unrelvar							-1.085		1.616
Industry FE	yes			yes			yes		
Region FE	yes			yes			yes		
Weighted by	employment size			employment size			employment size		
R^2	0.074			0.074			0.075		
Adjusted R^2	0.071			0.072			0.073		
N	22,788			22,788			22,788		

*** Significant at the 1% level
** Significant at the 5% level
*Significant at the 10% level

Table 4: Fixed effects regressions on the effects of labour mobility on productivity growth for all plants with inflow of skilled workers based (revealed relatedness)

PRODUCTIVITY GROWTH	MODEL C1			MODEL C2			MODEL D1			MODEL D2		
	Estimate		S.E	Estimate		S.E	Estimate		S.E	Estimate		S.E
Intercept	-3.149	***	0.768	-3.144	***	0.793	-3.086	***	0.795	-3.214	***	0.795
Year 2003	-0.177		0.228	-0.171		0.228	-0.175		0.228	-0.186		0.228
Year 2002	-0.018		0.227	-0.033		0.227	-0.019		0.227	-0.052		0.227
Year 2001	-1.504	***	0.223	-1.533	***	0.223	-1.497	***	0.223	-1.538	***	0.223
Year 2000	0.340		0.218	0.329		0.219	0.218		0.218	0.342		0.218
Year 1999	*Benchmark*			*Benchmark*			*Benchmark*			*Benchmark*		
Growth of Labour (log)	0.122	***	0.023	0.122	***	0.023	0.123	***	0.023	0.118	***	0.023
Growth of Assets (log)	0.157	***	0.006	0.157	***	0.006	0.157	***	0.006	0.158	***	0.006
Plant Size (log)	0.516	***	0.100	0.477	***	0.097	0.524	***	0.098	0.483	***	0.096
Firm Age (log)	0.864	***	0.111	0.863	***	0.111	0.854	***	0.111	0.851	***	0.111
High Education Ratio	1.235	*	0.670	0.974		0.664	1.262	*	0.668	0.962		0.662
Inhouse Same	0.847	*	0.454	0.774	*	0.456	0.826	*	0.452	0.842	*	0.456
Inhouse Sim	0.096		0.470	-0.009		0.488	0.141		0.467	-0.07 0		0.487
Inhouse Relvar	-0.137		0.648	-0.918		0.693	-0.120		0.672	-0.81 0		0.691
Inhouse Unrelvar	0.249		0.645	0.534		0.677	0.228		0.645	0.626		0.673
Total Skilled Inflow (log)	-0.512	***	0.127									
Total Intra Skilled Inflow (log)							-0.600	***	0.116			
Total Inter Skilled Inflow (log)							0.073		0.123			
Inflow Sim (log)				-0.253	**	0.113						
Inflow Relvar (log)				0.234	*	0.130						
Inflow Unrelvar (log)				-0.475	***	0.126						
Intra Inflow Sim (log)										-0.271	**	0.118
Intra Inflow Relvar (log)										-0.032		0.138
Intra Inflow Unrelvar (log)										-0.316	**	0.128
Inter Inflow Sim (log)										0.348	**	0.162
Inter Inflow Relvar (log)										0.848	***	0.203
Inter Inflow Unrelvar (log)										-0.582	***	0.156
Industry FE	yes			yes			yes			yes		
Region FE	yes			yes			yes			yes		
Weighted by	employment size			employment size			employment size			employment size		
R^2	0.073			0.073			0.075			0.075		
Adjusted R^2	0.070			0.071			0.072			0.073		
N	22,788			22,788			22,788			22,788		

*** Significant at the 1% level
** Significant at the 5% level
*Significant at the 10% level

Appendix I

Table 5: Municipalities and labour Markets

labour MARKET	MUNICIPALITIES
1	Copenhagen Frederiksberg Ballerup Brøndby Dragør Gentofte Gladsaxe Glostrup Herlev Albertslund Hvidovre Høje-Taastrup Ledøje-Smørum Lyngby-Taarbæk Rødovre Søllerød Ishøj Tårnby Vallensbæk Værløse Allerød Birkerød Farum Fredensborg-Humlebæk Frederikssund Frederiksværk Græsted-Gilleleje Helsinge Helsingør Hillerød Hundested Hørsholm Jægerspris Karlebo Skibby Skævinge Slangerup Stenløse Ølstykke Bramsnæs Greve Gundsø Hvalsø Køge Lejre Ramsø Roskilde Skovbo Solrød ValløRingsted Fakse Rønnede Stevns Bjergsted Dragsholm Holbæk Jernløse Nykøbing-Rørvig Svinninge Tornved Trundholm Tølløse Dianalund Gørlev Hashøj Hvidebæk Høng Kalundborg Korsør Skælskør Slagelse Sorø Stenlille Møn Fuglebjerg Haslev Fladså Holmegaard Langebæk Næstved Præstø Suså Vordingborg Christiansø
2	Højreby Nakskov Ravnsborg Rudbjerg Holeby Maribo Nykøbing F. Nysted Nørre-Alslev Rødby Sakskøbing Stubbekøbing Sydfalster
3	Allinge-Gudhjem Hasle Nexø Rønne Aakirkeby
4	Assens Bogense Broby Ejby Faaborg Glamsbjerg Haarby Kerteminde Langeskov Middelfart Munkebo Nyborg Nørre-Aaby Odense Otterup Ringe Ryslinge Søndersø Tommerup Ullerslev Vissenbjerg Ørbæk Årslev Aarup Egebjerg Gudme Svendborg Rudkøbing Sydlangeland Tranekær
5	Marstal Ærøskøbing
6	Gram Haderslev Nørre-Rangstrup Rødding Vojens Bov Lundtoft Rødekro Tinglev Aabenraa Christiansfeld
7	Augustenborg Broager Gråsten Nordborg Sundeved Sydals Sønderborg
8	Bredebro Højer Løgumkloster Skærbæk Tønder
9	Blåbjerg Blåvandshuk Bramming Brørup Esbjerg Helle Holsted Ribe Varde Fanø Vejen Grindsted Ølgod
10	Fredericia Gedved Horsens Juelsminde Kolding Lunderskov Vamdrup Billund Børkop Egtved Give Hedensted Jelling Nørre-Snede Tørring-Uldum Vejle Brande
11	Herning Ikast Trehøje Videbæk Åskov
12	Aulum-Haderup Holstebro Struer Thyholm Ulfborg-Vemb Vinderup
13	Lemvig Thyborøn-Harboøre
14	Holmsland Ringkøbing Egvad Skjern
15	Samsø
16	Brædstrup Grenaa Nørre-Djurs Langå Nørhald Purhus Randers Rougsø Sønderhald Bjerringbro Hvorslev Gjern Silkeborg Them Kjellerup Ebeltoft Galten Hadsten Hammel Hinnerup Hørning Midtdjurs Odder Rosenholm Ry Rønde Skanderborg Århus Fjends Skive Spøttrup Sundsøre Karup Møldrup Tjele Viborg
17	Morsø Sallingsund
18	Sydthy Hanstholm Thisted
19	Frederikshavn Sæby Hirtshals Hjørring Løkken-Vrå Sindal
20	Læsø
21	Skagen
22	Mariager Hobro Nørager Aalestrup Arden Brovst Brønderslev Dronninglund Fjerritslev Hadsund Hals Nibe Pandrup Sejlflod Skørping Støvring Aabybro Aalborg Farsø Løgstør Aars

Appendix II

Table 6: Fixed effects regressions on the effect of competence portfolio based on industry experience on productivity growth for all plants with inflow of skilled workers (NACE relatedness)

PRODUCTIVITY GROWTH	MODEL A1			MODEL B1			MODEL B2		
	Estimate		S.E	Estimate		S.E	Estimate		S.E
Intercept	-1.978	***	0.505	-2.341	***	0.764	-2.501	***	0.772
Year 2003	-0.135		0.227	-0.085		0.229	-0.093		0.229
Year 2002	-0.009		0.227	-0.008		0.227	-0.013		0.227
Year 2001	-1.520	***	0.222	-1.508	***	0.223	-1.512	***	0.223
Year 2000	0.321		0.218	0.350		0.218	0.349		0.218
Year 1999	*Benchmark*			*Benchmark*			*Benchmark*		
Growth of Labour (log)	0.109	***	0.023	0.112	***	0.023	0.112	***	0.023
Growth of Assets (log)	0.155	***	0.006	0.156	***	0.006	0.156	***	0.006
Plant Size (log)	0.269	***	0.065	0.221	***	0.066	0.228	***	0.067
Firm Age (log)	0.871	***	0.109	0.845	***	0.111	0.839	***	0.111
High Education Ratio	0.264		0.627	0.301		0.630	0.288		0.631
Inhouse Same				1.054	**	0.483	1.192	**	0.488
Inhouse Sim				-0.431		0.459			
Inhouse Relvar				-0.662		0.742			
Inhouse Unrelvar				-0.121		0.590			
Intra Inhouse Sim							-0.631		0.474
Intra Inhouse Relvar							-0.424		0.759
Intra Inhouse Unrelvar							0.087		0.644
Inter Inhouse Sim							2.294		1.477
Inter Inhouse Relvar							-3.609		3.87
Inter Inhouse Unrelvar							-0.715		1.453
Industry FE	yes			yes			yes		
Region FE	yes			yes			yes		
Weighted by	employment size			employment size			employment size		
R^2	0.073			0.073			0.074		
Adjusted R^2	0.070			0.071			0.071		
N	22,788			22,788			22,788		

*** Significant at the 1% level
** Significant at the 5% level
*Significant at the 10% level

Appendix III

Table 7: Fixed effects regressions on the effects of labour mobility on productivity growth for all plants with inflow of skilled workers based (NACE relatedness)

PRODUCTIVITY GROWTH	MODEL C1 Estimate		S.E	MODEL C2 Estimate		S.E	MODEL D1 Estimate		S.E	MODEL D2 Estimate		S.E
Intercept	-2.998	***	0.780	-3.090	***	0.799	-3.116	***	0.790	-3.116	***	0.803
Year 2003	-0.142		0.229	-0.128		0.229	-0.140		0.229	-0.140		0.229
Year 2002	-0.020		0.227	-0.020		0.227	-0.006		0.227	-0.006		0.227
Year 2001	-1.509	***	0.223	-1.504	***	0.223	-1.479	***	0.223	-1.479	***	0.223
Year 2000	0.335		0.218	0.340		0.218	0.370	*	0.218	0.370	*	0.219
Year 1999	*Benchmark*			*Benchmark*			*Benchmark*			*Benchmark*		
Growth of Labour (log)	0.122	***	0.023	0.125	***	0.023	0.123	***	0.023	0.124	***	0.023
Growth of Assets (log)	0.157	***	0.006	0.157	***	0.006	0.157	***	0.006	0.158	***	0.006
Plant Size (log)	0.539	***	0.101	0.470	***	0.099	0.542	***	0.098	0.463	***	0.097
Firm Age (log)	0.864	***	0.111	0.869	***	0.111	0.855	***	0.111	0.864	***	0.111
High Education Ratio	1.243	*	0.669	1.023		0.666	1.265	*	0.666	0.971		0.665
Inhouse Same	0.599		0.495	0.749		0.493	0.598		0.493	0.802		0.493
Inhouse Sim	0.042		0.472	-0.047		0.489	0.081		0.470	-0.122		0.489
Inhouse Relvar	-0.704		0.742	-0.667		0.780	-0.674		0.741	-0.692		0.778
Inhouse Unrelvar	0.285		0.598	0.186		0.621	0.279		0.598	0.299		0.618
Total Skilled Inflow (log)	-0.535	***	0.128									
Total Intra Skilled Inflow (log)							-0.603	***	0.116			
Total Inter Skilled Inflow (log)							0.050		0.124			
Inflow Sim (log)				-0.213	*	0.111						
Inflow Relvar (log)				-0.210		0.155						
Inflow Unrelvar (log)				-0.234	*	0.123						
Intra Inflow Sim (log)										-0.250	**	0.116
Intra Inflow Relvar (log)										-0.265		0.168
Intra Inflow Unrelvar (log)										-0.229	*	0.124
Inter Inflow Sim (log)										0.376	**	0.162
Inter Inflow Relvar (log)										0.696	**	0.296
Inter Inflow Unrelvar (log)										-0.260	*	0.146
Industry FE	yes			yes			yes			yes		
Region FE	yes			yes			yes			yes		
Weighted by	employment size			employment size			employment size			employment size		
R^2	0.074			0.074			0.074			0.075		
Adjusted R^2	0.071			0.071			0.072			0.072		
N	22,788			22,788			22,788			22,788		

*** Significant at the 1% level
** Significant at the 5% level
*Significant at the 10% level